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Region Based Integrated Approach for Image Retrieval

[1]TALLURI. SUNIL KUMAR, [2]T.V.RAJINIKANTH , [3]B. ESWARA REDDY
[1]VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India
[2]SNIST, Hyderabad, Telangana India.
[3]Professor in CSE and Principal, JNTU-A College of Engineering, Kalikiri, Chittoor Dist, Andhra. Pradesh, India.
Email: [1]sunilkumart1973@gmail.com, [2]rajinitv@gmail.com, [3]eswarcsejntua@gmail.com,

Abstract

This paper proposes an integrated method for efficient content based image retrieval using color, shape and rotational invariant texture features. The present paper derived rotational invariant features on each region. To derive shape features textons are computed. To represent texture features gray level co-occurrence matrix (GLCM) features are derived on region based rotational invariant texton matrix. These features are combined with HSV histograms. The advantage of region based models is they are more applicable when working with images of large size and especially in real time environment. The image retrieval is performed on five categories of Wang database and the present method is compared with texton co-occurrence matrix (TCM), color correlogram gradient (CCG) and GLCM methods.

Keywords: *GLCM, HSV; shape; texture; rotation invariant features;*

1. Introduction

These days there is a huge expansion on browsing of the digital libraries or databases. Searching and retrieving images from these libraries has become a crucial and tedious task for human annotation and this has created the dire need of content based image retrieval (CBIR) methods. The CBIR methods are capable of retrieving the desired images from these libraries based on the image contents. The CBIR models makes use of visual contents of an image like color, shape, texture mosaic, faces and spatial layouts for efficient image retrieval (IR). It is highly impossible to represent an image with a single best feature and it is due to the fact that user may capture photographs from different angles, lighting conditions, reflection etc. The traditional image retrieval (IR) methods are text based methods. The images are retrieved by matching the corresponding index text or meta-data associated with images. A comprehensive literature survey on CBIR is presented in [1-4].

The color content of an image is one of the powerful descriptor of CBIR and it can keep semantically intact and it is robust to noise, change in size, image degradation and orientation. There are various CBIR systems that are based on color descriptors [5, 6, 7, 8]. The retrieval performance of these degrades on huge databases due to color shading problems. One of the most visual characteristic feature of the image is the texture and texture features plays an important and crucial role in many applications like image classification [9, 10, 11], face recognition [12, 13], smoke detection [14], age and facial expressions identification [15, 16], pedestrian detection [17, 18] and image retrieval[19, 20, 21, 22, 23]. Various methods are proposed for extracting texture features such as co-occurrence matrices [24], local binary patterns [25, 26], textons [27] and pattern based methods [28, 29]. These methods can be roughly classified into statistical, structural and model based method. Most of the pattern based methods attempted to retrieve the desired images based on the frequencies of each pattern in the image and treated them as feature descriptor using histograms. The frequency gives information regarding the number of times these patterns appeared in the image and it doesn't not reveal any information regarding the mutual occurrence of patterns in the image. This is addressed by the present paper by making use of textons.

The IR based on texture descriptors such as Gabor transforms [30], rotated wavelet filters [31] are proposed in the literature. The other CBIR models are based on relevance feedback techniques [32], robust local patterns [33], temporal patterns of video sequences [34] and the combination of relevance feedback with region based features [35]. Recently various pattern based features i.e. local maximum edge patterns [36], local tetra patterns [37] for natural IR are proposed. The pattern based features are also proposed for retrieving of medical images i.e. directional binary wavelet pattern [38], local mesh patterns [39] and local ternary co-occurrence patterns [40]. The block based methods using LBP texture descriptors are proposed by Takalo et al. [41] for CBIR. The present paper divides the image into multi regions and evaluates the features on each region. This provides the detailed relative location similarity and

reduces the computational complexity. The earlier works on CBIR treated the texture and color information as individual features. In this work region based rotational invariant texture features are integrated with shape and color space components for efficient image retrieval.

The present paper is organized as follows. The second section describes the concepts of basic LBP and generation of rotational invariant uniform LBP. The section three describes the methodology and frame work. The section four and five gives the results and discussions and conclusions.

2. Local binary pattern (LBP)

Ojala et al. [42] introduced a powerful local gray scale descriptor called LBP for texture classification. LBP utilizes the intensity distribution of local neighborhood pixels. The LBP code on a neighborhood is computed by comparing the greyscale value of neighboring pixels (g_p) with central pixels (g_c) as shown in the Figure 1, based on the following equations.

$$LBP_{P,R} = \sum_{P=1}^{P=8} 2^{(P-1)} * s(g_p - g_c) \quad (1)$$

$$s(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; otherwise \end{cases} \quad (2)$$

Where P is the number of neighboring pixels and R is the radius of the neighborhood. A 3x3 neighborhood will have P=8 and R=1. The co-ordinates of the neighborhood pixels are computed as (RCos(2πP/P, -RSin(2πP/P) and their grey levels are estimated by interpolation.

25	45	92
89	55	102
17	29	110

(a)3x3 neighborhood, P=8,R=1

0	0	1
1		1
0	0	1

(b)Binary pattern based on eq.2

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(c)Corresponding weights

156

(d)LBP code generation

Figure 1: LBP code generation.

2.1 Derivation of Rotational Invariant ULBP ($ULBP^{ri}$)

LBP with P neighboring pixels results into 2^P combinations of LBPs. This results a feature vector length of 2^P. As the number of neighboring pixels increases (16, 1) and (16, 2) the length of feature vector increases drastically. The disadvantage of this feature vector is its computational cost. To overcome this uniform LBP (ULBP) [43, 44] are proposed. The ULBPs have limited discontinues i.e. less than or equal to two in the circular binary representation and it is proved that most of the windows (above 90%) in human faces and textures are ULBPs. The remaining patterns where the numbers of transitions from 0 to 1 or 1 to 0 are above two are considered as non-ULBPs (NULBP). The NULBPS are treated as miscellaneous. There will be P*(P-1) +3 distinct ULBP on a neighborhood with P neighboring pixels.

The $LBP_{8,1}$ operator produces 2^8 different binary patterns and this results a total of 256 LBP codes or feature vector of length 256. When the image is rotated, the gray level values of P_i will correspondingly move along the perimeter of the circle around, the central pixel P_c. The pixel P_1 of the neighborhood is mostly assigned the co-ordinate position (0, 0) as shown in Figure 2. Rotating a particular binary pattern on the perimeter naturally results different LBP_8 codes. This does not apply to the constant binary pattern i.e. contains all zeros or all ones (00000000 or 11111111).To overcome this rotation effect and to make the local binary pattern as rotation invariant a unique identifier is denoted by obtaining the minimum or maximum value by rotating as given in equation 3 and 4.

$$LBP_8^{ri} = min\{ROR(LBP_8, i) \mid i = 0,1 \dots 7\} \quad (3)$$

or

$$LBP_8^{ri} = max\{ROR(LBP_8, i) \mid i = 0,1 \dots 7\} \quad (4)$$

Where ROR(z,i) performs a circular bitwise right shift on the 8-bit binary number z, i times. The min(x) or max(x) takes out the minimum or maximum LBP code from these 8- circular shifts. This becomes the rotation invariant LBP (LBP^{ri}).

(0,0)	(0,1)	(0,2)
(1,0)	(1,1)	(1,2)
(2,0)	(2,1)	(2,2)

Figure 2: The basic co-ordinate system of a LBP window.

Table 1: $ULBP^{ri}$ values and indexes on $LBP_{8,R}$.

Rotational invariant ULBP on a 3 x 3 window (adjacent 1s)	LBP code Value according to equation 3	Index value assigned to $ULBP^{ri}$
(0000 0001)	1	1
(00000011)	3	2
(00000111)	7	3
(00001111)	15	4
(00011111)	31	5
(00111111)	63	6
(01111111)	127	7
(11111111)	255	8
(00000000)	0	9
All others-NULBPS		0

There are 36 unique rotation invariant LBPs that occur on a 3x3 neighborhood or $LBP_{8,R}$. It is experimentally shown that $LBP_{8,R}^{ri36}$ does not show any good discrimination [44]. The performance of these 36 patterns in discrimination of textures varies greatly because some patterns sustain rotation quite well while other patterns do not and confuse the analysis.

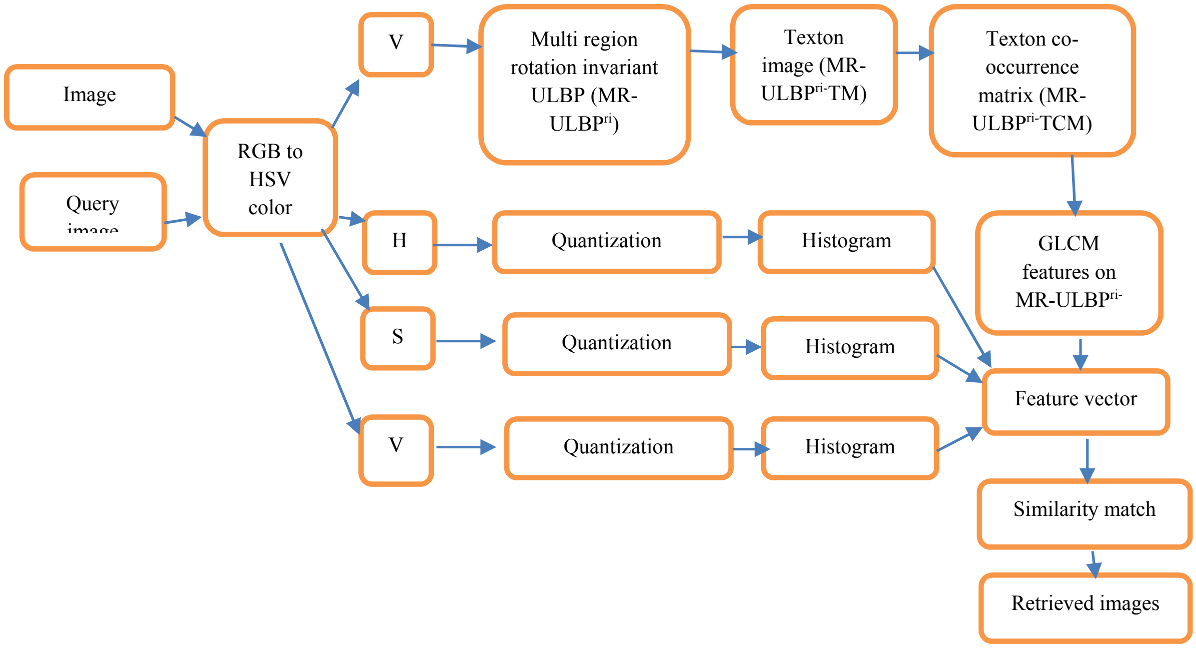


Figure 3: The integrated CBIR model of the present paper

The varying performance of these LBP^{ri} also led to the discovery of uniform (U) patterns. A ULBP appears on a $LBP_{8,R}$, whenever there are zero or more (<= 8) adjacent ones in any position and the Table1 summarizes the index values that are assigned to ULBP^{ri} by the present paper.

3. Methodology

The present paper proposes a novel frame work for CBIR called "multi-region rotational invariant uniform LBP texton matrix" (MR-ULBP^{ri}-TM) to overcome the limitations of LBP, and to capture shape information on multi regions. The basic image retrieval model of this paper is given in Figure 3.

The basic LBP operator has the following disadvantages. It is designed for a small spatial support area (3 x 3 neighborhood); therefore the bit-wise comparison between two single pixel values of this neighborhood is affected by noise to a great extent. The features computed on the basic LBP cannot capture larger scale structure (macrostructure) that may have dominant features of textures. In this paper the computation on sub regions is performed based on average values of sub regions, instead of individual pixels.

3.1. Computation of MR-ULBP^{ri}

The present paper converts the color image in to HSV color space and derives color histograms. The V color space of the image is divided into non over-lapped regions of size 9x9. Each region is sub divided into nine non overlapped sub-regions. The present multi region (MR) IR model derives a single value for each rectangular sub region. The advantage of the present method is it reduces the overall dimension space of the derived features. The MR model captures the dominant features on a large scale rectangular structure and the sub region features are estimated on grey level values of a local neighborhood. The steps for computation of MR-ULBP^{ri} are given below.

Step one: Replace the each sub region by its average grey level value. By this the region of size 9 x 9 with 9 sub regions becomes a 3 x 3 neighborhood, where each pixel value represents the average grey level value of that sub region.

Step two: Computation of LBP on each region by average operator. The comparison operator between single pixels in LBP is simply replaced with comparison between average gray-values of sub-regions (threshold). This generates a binary pattern.

Step Three: If the generated multi region-Local binary pattern of step two is ULBP then replace the central pixel with MR-ULBP^{ri} index value as given in table 1. Otherwise replace the central pixel with value zero (NULBP).

Note that the scalar values of averages over blocks can be computed very efficiently [45] from the summed-area table [46] or integral image [47]. For this reason, MR-ULBP^{ri} feature extraction can also be very fast: it only incurs a little more cost than the original 3 × 3 LBP operator. This way, MR-ULBP^{ri} code presents several

advantages: (1) It is rotational invariant and robust; (2) it encodes not only micro structures but also macrostructures of image patterns, and hence provides a more complete image representation than the basic LBP operator; (3) MR-ULBP^{ri} can be computed very efficiently using integral images. 4) This representation is very useful in deriving textons because the image is quantized to ten levels (0 to 9); the ULBP^{ri} will be given indexes from 1to 9 and all NULBPs as zero.

The regions can be small, medium and large i.e. 3 × 3, 9 × 9 and 15 × 15 neighborhoods respectively. For a small scale regions like basic LBP, local, micro patterns of textures are well represented, which may beneficial for discriminating local details. On the other hand, using average values over the large scale regions (15 x 15) reduce noise, and makes the representation more robust; and large scale information provides complementary information to small scale details and much discriminative information is also dropped. Normally, regions of various scales should be carefully selected and then fused to achieve better performance. The present paper chose a region of size 9 x 9 and sub regions of size 3 x 3.

3.2. Computation of "Texton Matrix on Multi Region Rotational Invariant Uniform LBP (MR-ULBP^{ri}-TM)"

The previous section generates a multi-region based ULBP^{ri} (MR-ULBP^{ri}) image with ten quantized levels or patterns {0 to 9}. The present section evaluates textons on this. The LBP and texton based models are widely used in many applications [48, 49, 50, 51]. It is found that, it is very difficult to obtain satisfactory results, of image processing, by designing algorithms that process the images based on pixel levels. More over this processing system fail in representing the shape component totally. To address this Julesz [27] proposed the concept of texton's. Textons represent the relationship between pixels in the form of shape component; however defining a texton is still a difficult task. Texton is one of the popular and significant shape primitives and is defined with certain placement rule. The textons represents the emergent and dominant patterns on a local neighborhood.

The image features have a close relationship with textons and color diversification. The difference textons may form various image features. If the textons in image are small and the tonal differences between neighboring textons are large, a fine texture may result. If the textons are higher and holds quite a few pixels then it results a coarse texture and it also depends on scale [49]. In the image if the textons are large and contains a small number of texton categories, then a shape may result. There can be numerous types of textons in image. In this paper, we only classify and make use of five special types of textons that holds all the three or four neighboring pixels on a 2 x 2 windows or grid. The pixels of the grid are denoted as P, Q, R and S. The five types of textons are denoted as A_1, A_2, A_3, A_4 and A_5 (Figure 4).

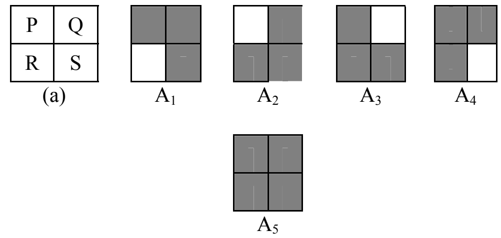
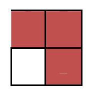


Figure 4: The textons used in this paper (a) 2x2 window of the image A_1 to A_5 : different textons.

0	1	2	4	4	8	9
2	1	1	8	5	9	9
4	4	7	5	5	8	8
4	4	2	2	1	0	8
5	0	4	2	8	0	3
5	5	7	7	5	6	6
2	1	7	9	9	6	8

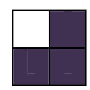
(a)

A_1



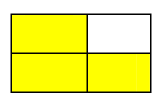
0	0	0	0	0	0	0
0	0	0	0	0	0	0
4	4	0	0		8	8
0	4	0	0	0	0	8
0	0	0	0	0	0	0
0	0	7	7	0	0	0
0	0	0	7	0	0	0

A_2



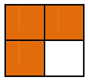
0	0	0	0	0	0	9
0	0	0	0	5	9	9
0	4	0	5	5	0	0
4	4	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

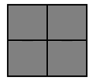
A_3



0	1	0	0	0	0	0
0	1	1	0	0	0	0
4	0	0	0	0	0	0
4	4	0	0	0	0	0
5	0	0	0	0	0	0
5	5	0	0	0	0	0
0	0	0	0	0	0	0

(b)

A_4 

A_5 

0	0	0	0	0	0	0
0	0	0	0	0	0	0
4	4	0	0	0	0	0
4	4	0	0	0	0	0
0	0	0	0	0	0	0
0	0	7	7	0	6	6
0	0	7	0	0	6	

0	0	0	0	0	0	0
0	0	0	0	0	0	0
4	4	0	0	0	0	0
4	4	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

(c)

0	1	2	4	4	8	9
2	1	1	8	5	9	9
4	4	7	5	5	8	8
4	4	2	2	1	0	8
5	0	4	2	8	0	3
5	5	7	7	5	6	6
2	1	7	9	9	6	8

(d)

Figure 5: computation of MR-ULBP^{ri}-TM from MR-ULBP^{ri}image. (a):MR-ULBP^{ri} image ; (b):Detection of textons A_1, A_2 and A_3 on MR-ULBP^{ri} image (c)Computation of textons A_4 and A_5 on MR-ULBP^{ri} image; (d)Formation of MR-ULBP^{ri}-TM (Final Texton image) using A_1, A_2, A_3, A_4 and A_5.

The process of texton identification is shown in Figure 5.The present paper used the five types of textons to detect every grid. A particular texton detection process is performed on a 2 x 2 grid in overlapped manner (shifting right by one column position then row by one position down) and if the texton is detected the pixels of texton are kept with original values and others are replaced with zeros. The same process is repeated for all five defined categories of textons. The MR-ULBP^{ri}-TM (final texton) image (Figure 5(d) will be formed by combining these five types of texton images (Figure 5(b) &5 (c).

3.3 COMPUTATION OF GLCM FEATURES ON MR-ULBP^{ri}-TM

On MR-ULBP^{ri}-TM image, the co-occurrence matrix is formed with a distance D and with an angle 0^0,45^0,90^0 and 135^0. The GLCM features i.e. entropy, energy, contrast, local homogeneity and correlation (equations 5.6,7,8 and 9) are computed on MR-ULBP^{ri}-TM with 0^0,45^0,90^0 and 135^0 orientations and average feature values of these orientation are listed in the feature library.In order to extract color information the present paper also quantized the original image using HSV color space.

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \quad (5)$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \quad (6)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}\,(i-j)^2 \quad (7)$$

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (8)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (9)$$

where P_{ij} is the pixel value in position (i,j) of the texture image, N is the number of gray levels in the image, μ is $\mu = \sum_{i,j=0}^{N-1} iP_{ij}$ mean of the texture image and σ^2 is $\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}\,(i-\mu)^2$ variance of the texture image.

3.4 Image Retrieval Algorithm

The proposed image retrieval algorithm is given below

Input: Query image Output; Retrieval of similar images

1. Convert the RGB image into HSV color space.
2. Divide the v-color space image into non overlapped regions of size 9 x 9.
3. Divide the region in to sub regions and derive feature vector (The region of sixe 9 x 9 becomes 3 x 3).
4. Derive multi region rotational invariant ULBP (MR-ULBP^{ri}) index (as given in table 1) image.
5. Compute texton matrix on multi-region rotational invariant ULBP (MR-ULBP^{ri}-TM) by deriving textons on each 2x2 grid of step 4.
6. Derive multi-region rotational invariant ULBP texton co-occurrence matrix (MR-ULBP^{ri}-TCM) with various distances on step 5.
7. Compute GLCM features on MR-ULBP^{ri}-TCM.
8. Compute the histograms for H, S and V color spaces.
9. Construct feature vector by concatenating histograms for H, S and V color spaces with MR-ULBP^{ri}-TCM features.
10. Compare the features of query image with the images in the database using similarity measurement.
11. Retrieve the images based on nearest distance or best matches.

3.5 Query Matching

This is accomplished by measuring the distance between the query image and database images. The present paper used Euclidean distance as the distance measure and as given below

$$Dist_s(T_n, I_n) = \left(\sum_{i,j=1} \left|f_i(T_n) - f_j(I_n)\right|^2\right)^{1/2} \quad (10)$$

Where T_n query image, I_n image in database;

The database image is used as the query image in our experiments. If the retrieved image belongs to the same category as that of query image we say that the system has suitably identified the predictable image otherwise the system fail to find the image.

4. Results and Discussion

In order to efficiently investigate the performance of the present retrieval model, we have considered the Wang database [52]. Wang is a subset of Corel stock photo database. In the Wang database the images have been manually chosen. This data base consists of 5 classes of images i.e. Elephants, Fancy Flowers, Horses, Valleys and Evening Skies and 100 images per each class. The present paper used these 5 classes of images for relevance assessment. For a query image the relevant images are assumed to be the remaining 99 images of the same class. The images from all other classes are treated as irrelevant images. The hefty size of each class and the heterogeneous image class contents made Wang data base as one of the popular database for image retrieval. The performance of the present model is evaluated in terms of precision and recall rate. Precision is the ratio of number of retrieved images (I_{NR}), Vs. the number of relevant images retrieved (**I_{RR}**). The recall is the ratio of total number of relevant images in the database (I_{TR}) Vs. I_{RR}.

$$\text{Precision - } P = (I_{RR} \ / I_{NR}) \qquad (11)$$

$$\text{Recall } -R = (I_{RR} \ / I_{TR}) \qquad (12)$$

The present paper compute GLCM features on MR-ULBP^{ri}-TCM using various distance values: $D = 1, 2 \ldots 7$ and query matching is performed using Euclidean distance. The present retrieval model selects 16 top images from the database images that are matching with query image. And also experimented with more number of top images and retrieval performance is measured. Figure 6 shows five examples of retrieval images, i.e. one image from each class, by the proposed method with D=4 for I_{NR} =16 and top left most image is the query image.

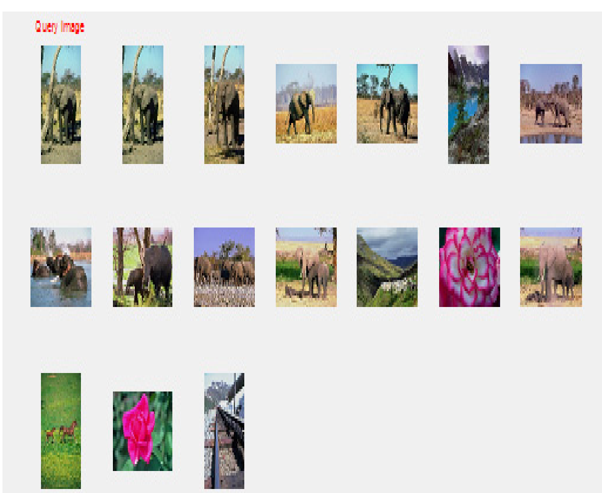


Figure 6 (a): Retrieved elephant images.

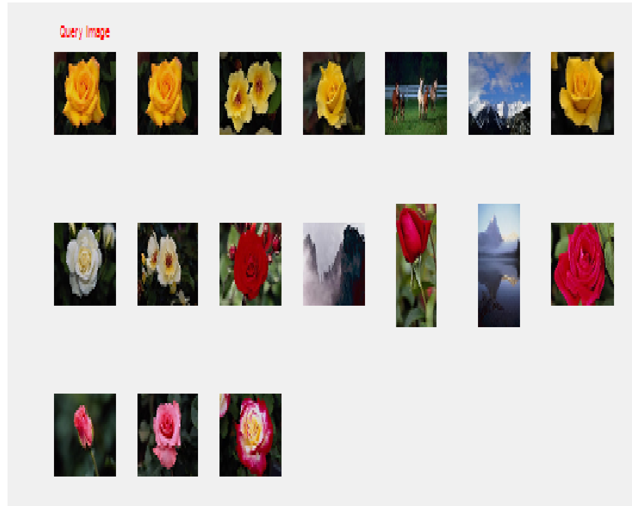


Figure 6 (b): Retrieved fancy flower images.

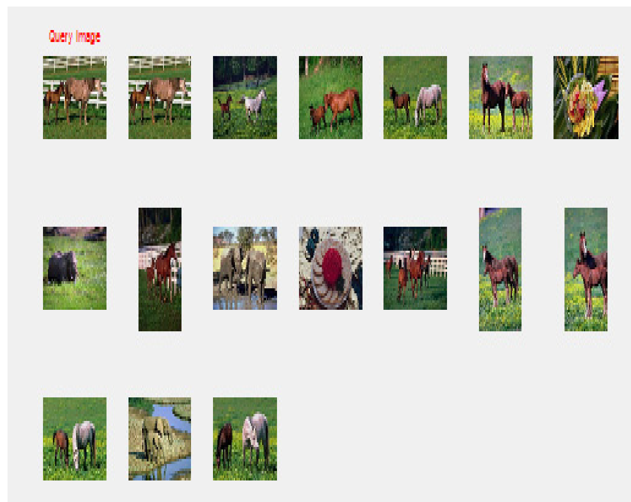


Figure 6(c): Retrieved horse images.

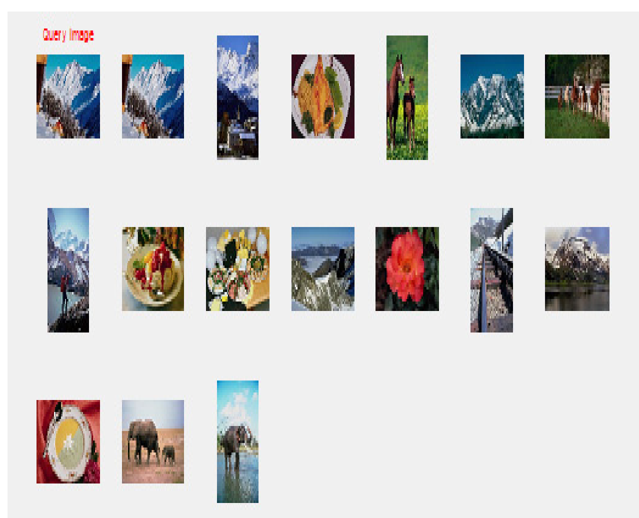


Figure 6 (d): Retrieved valley images.

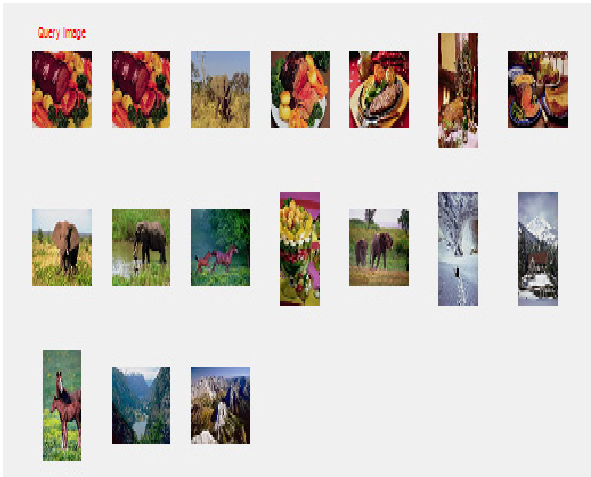


Figure 6 (e): Retrieved Evening Skies images.

Fig 6(a) to 6(e) Retrieved images for each class with D=4 for I_{NR} =16 on proposed integrated method.

The average precision and recall rates of all classes of images are computed based on MR-ULBP^{ri}-TCM features and color histograms and listed in Tables 2 and 3. The best performance of MR-ULBP^{ri}-TCM with color histograms was obtained when $D = 4$. The retrieval performance of the integrated MR-ULBP^{ri}-TCM is compared with GLCM [53], color correlogram [54] and texton Co-occurrence matrix [49]. The present paper selected 60 images of the same category or class as query images (one by one) and computed precession and recall rates by selecting top 16, 25, 35, 45, 55,65,75,85 and 95 images. The average precession rates of GLCM, CCG and TCM are ranging from 38% to 45%, 39% to 46% and 60% to 64% respectively for D=4 and for number of images retrieved I_{NR}=16 (Table 2 & 3). The average precession and recall rates are plotted in graphs (Figure 7 and 8) by varying I_{NR}. The present paper also computed image retrieval accuracy as defined below.

$$\text{IR accuracy A} = ((\text{precession} + \text{recall}) /2) \qquad (11)$$

Table 2: Average precision rate of all classes of images with various distance measures for I_{NR} =16.

Methods	Distance parameter						
	D=1	D=2	D=3	D=4	D=5	D=6	D=7
GLCM	0.38	0.41	0.42	0.45	0.44	0.43	0.43
CCG	0.39	0.41	0.44	0.46	0.45	0.44	0.43
TCM	0.60	0.61	0.63	0.64	0.63	0.61	0.62
Proposed MR-ULBP^{ri}-TCM	0.69	0.71	0.74	0.76	0.75	0.72	0.71

The average IR accuracy graph with varying number of matches considered (I_{NR}) is plotted (Figure 9). The proposed integrated MR-ULBP^{ri}-TCM achieved best performance when compared to the existing three methods.

Table 3: Average precession rate on each class of images for D=4 for I_{NR} =16.

Methods	Image category and the precision (%)					
	Elephants	Fancy Flowers	Horses	Valleys	Evening Skies	Average
GLCM	0.39	0.42	0.44	0.48	0.5	0.45
CCG	0.4	0.43	0.46	0.49	0.52	0.46
TCM	0.61	0.6	0.66	0.67	0.7	0.64
Proposed MR-ULBP^{ri}-TCM	0.71	0.72	0.76	0.81	0.82	0.76

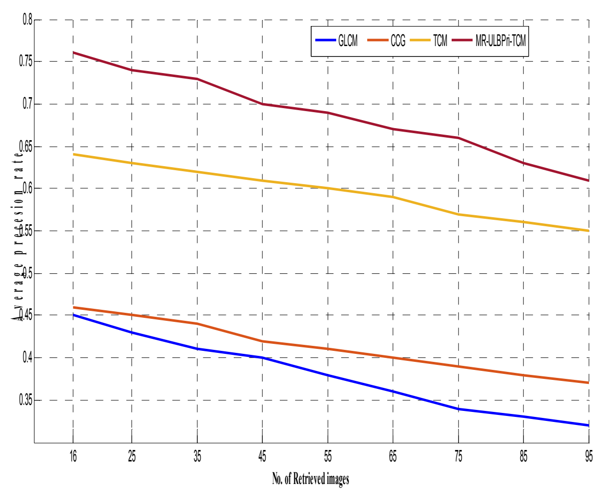


Figure 7: Average Performance curve (precision) using GLCM, CCG, TCM and MR-ULBP^{ri}-TCM method with D=4.

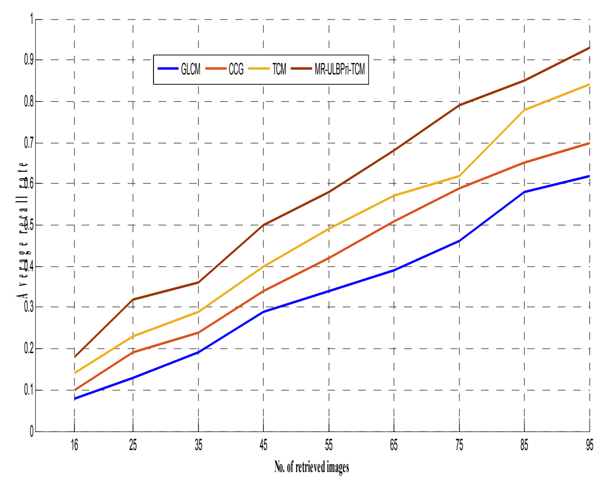


Figure 8.: Average Performance curve (recall) using GLCM, CCG, TCM and MR-ULBP^{ri}-TCM method with D=4.

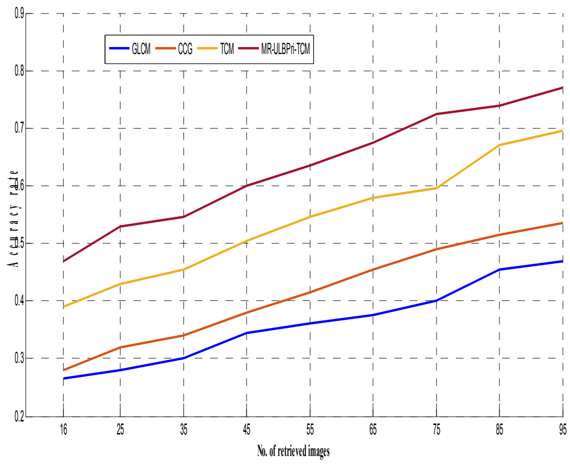


Figure 9: Average Performance curve (accuracy) using GLCM, CCM, TCM andMR-ULBP^{ri}-TCM method with D=4.

5. Conclusions

The proposed CBIR model integrated the features from texture, shape and color. The present paper derived a region based model and evaluated rotational invariant features in the form of ULBP^{ri}. The proposed model is robust and averages can be computed efficiently using integral images. The small feature set of multi region can make the overall process to be simple and suitable when dealing with large size images especially in real time environment. The rotational invariant ULBP indexing quantizes the image in to 10 levels and these are useful in computing texton matrix. The GLCM features derived on MR-ULBP^{ri}-TCM along with color histograms outperformed the earlier methods of image retrieval. The proposed method is carried out with varying distances and number of retrieved images. The proposed method shown high results of retrieval for D=4.

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Biographies

Talluri. Sunil Kumar received his M.Tech Degree in Computer Science & Engineering from Osmania University Hyderabad, Telangana State, India. He is an Associate Professor in Computer Science & Engineering Department, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana State, India. He Published 2 publications in various National and International Journals/Conferences. Organised International Conferences. His main research interest includes, Data Mining Image Processing, Cloud Computing, Machine Learning. He is a life member of CSI, ISTE.

Dr. T.V.Rajinikanth received M.Tech Degree in Computer Science & Engineering from Osmania University Hyderabad, Telangana, India and he received PhD degree from Osmania University Hyderabad, Telangana, India. He is Professor of Computer Science & Engineering Department, SNIST, Hyderabad, Telangana, India. Published more than 50 publications in various National and International Journals/Conferences. Organised and Program Chaired 2 International Conferences,2 grants received from UGC,AICTE . Editorial Board Member for several International Journals. Received Best Paper Award : "Design and Analysis of Novel Similarity Measure for Clustering and Classification Of High Dimensional Text Documents" in the Proceedings of 15th ACM-International Conference on Computer Systems and Technologies (CompSysTech-2014),pg:1-8,2014, Ruse, Bulgaria, Europe. His main research interest includes Image Processing, Data Mining, Machine Learning.

Dr. B. Eswara Reddy Graduated in B.Tech.(CSE) from Sri Krishna Devaraya University in 1995. He received Masters Degree in M.Tech.(Software Engineering), from JNT University, Hyderabad, in 1999. He received Ph. D in Computer Science & Engineering from JNT University, Hyderabad, in 2008. Currently, he is working as Professor in CSE Department & Principal of JNTU-A College of Engineering, Kalikiri , Chittoor Dist A.P, India . He has published more than 100 publications in National and International Conferences and Journals. His research interests include Pattern Recognition & Image Analysis, Data Mining, and Cloud Computing. He received UGC Major Research Project titled 'Cloud Computing Framework for Rural Health Care in Indian Scenario'. He is Co-author of the text books 'Programming with Java' (Pearson/Sanguine) and 'Data Mining' (Elsevier India). He is a life member of CSI, ISTE, ISCA, Fellow-IE (India) and member of IEEE